adversarial text mining for speculative sentiment classification

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Abstract

Keywords:

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1. Introduction

GAN utilizes the minimax game theory to generate plausible fake data samples, and has been commonly applied in data augmentation areas such as images, video and texts. Unlike the vanilla GAN that has no control on modes of the data being generated, the proposed model is flexible enough to condition on arbitrary information that is necessary to draw the speculative similar documents (SSD should be explained before). Specifically, the proposed model consist of two components: generator, discriminator and collaborator. For the generator, given an anchor, the goal is to sample candidate documents from the repository. the sampling of the candidate documents are conditioned on necessary information such as class (similar or dissimilar), and the user, item and texts of the anchor document. Therefore, a well-trained generator is expected to output the most plausible documents to our advantage. For example, when the class is set to 1 (similar), the generator can output documents that have the same ground-truth sentiment as the anchor document, and we can incorporate those speculative similar documents for improving classification performance. The discriminator, on the contrary, plays the role of a classifier that focuses on discriminating whether an document is fake from the generator or is real from the original dataset. The generator and the discriminator are trained in an adversarial manner until an equilibrium state is reached, where the discriminator can no longer distinguish whether a document is fake or real. Finally, the collaborator incorporates the speculative similar documents provided by the generator into a collaborative filtering framework, and learns better representations for the users, items and documents, which in turn benefits the learning of generator and discriminator.

for a given input $< u_i, v_j, d_{ij} >$, where d_{ij} denotes the document that user u_i writes about v_j, the primary goal of the proposed model is to determine the overall sentiment of d_{ij}. For speculative sentiment classification, one subgoal is

for a candidate document, the discriminator simultaneously determine

for discriminator:

$$\mathbb{E}_{d_k \sim P(d|d_{ij},s)} log[D_\phi(d_k, d_{ij}, s)] + \mathbb{E}_{d'_k \sim P_{G_\theta(d|d_{ij},s)}} log[D_\phi(d'_k, d_{ij}, s)] \tag{1}$$

$\mathbb{E}$

$$\mathcal{L}_1^D = \mathbb{E}_{d_k \sim P(d|d_{ij},s)} - logf_1^D(d_k, d_{ij}) \tag{2}$$

$$\mathcal{L}_2^D = \mathbb{E}_{d'_k \sim P_{G_\theta(d|d_{ij},s)}} - log[1 - f_1^D(d'_k, d_{ij})] \tag{3}$$

$$\mathcal{L}_3^D = \mathbb{E}_{d_k \sim P(d|d_{ij},s)}[s * logf_2^D(d_k, d_{ij}) + (1 - s) * log(1 - f_2^D(d_k, d_{ij}))] \tag{4}$$

$$\mathcal{L}_4^D = \mathbb{E}_{d'_k \sim P_{G_\theta(d|d_{ij},s)}}[s * logf_2^D(d'_k, d_{ij}) + (1 - s) * log(1 - f_2^D(d'_k, d_{ij}))] \tag{5}$$

for generator:

$$\mathcal{L}_1^G = \mathbb{E}_{d'_k \sim P_{G_\theta(d|d_{ij},s)}} - logf_1^D(d'_k, d_{ij}) \tag{6}$$

$$\mathcal{L}_2^G = \mathbb{E}_{d'_k \sim P_{G_\theta(d|d_{ij},s)}}[s * logf_2^D(d'_k, d_{ij}) + (1 - s) * log(1 - f_2^D(d'_k, d_{ij}))]) \tag{7}$$

for distribution $P_{G_\theta(d|d_{ij},s)}$:

$$P_{G_\theta(d|d_{ij},s)} = \frac{expf^G(d_{ij}, d, s)}{\sum_{k=1}^K expf^G(d_{ij}, d_k, s)} \tag{8}$$

the generated documents have to satisfy two requirements, (1)semantically similar to the anchor document, (2) share the same sentiment with the anchor document.

2. Conclusion

3. policy gradient

$$R(\theta) = \sum_{s \in \{0,1\}} P_\theta(s|d_{ij}, d_k)V(s, d_{ij}, dk) \tag{9}$$

4. dcu

Algorithm 1 algpseudocode of l2c_ref_model

while not end **do**
    if not l2c_noc4_fifo.empty() **then**
        $req\_pkt \leftarrow$ l2c_noc4_fifo.pop();
    else if not l2c_noc2_fifo.empty() and not l2c_noc3_fifo.nearfull() **then**
        $req\_pkt \leftarrow$ l2c_noc2_fifo.pop();
    end if
end while